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Energy-Efficient Compressive Data Gathering Utilizing Virtual Multi-Input Multi-Output

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Abstract

Data gathering is an attractive operation for obtaining information in wireless sensor networks (WSNs). *But one of important challenges is to minimize energy consumption of networks. In this paper, an integration of distributed compressive sensing (CS) and virtual multi-input multi-output (vMIMO) in WSNs is proposed to significantly decrease the data gathering cost. The scheme first constructs a distributed data compression model based on low density parity check-like (LDPC-like) codes. Then a cluster-based dynamic virtual MIMO transmission protocol is proposed. The number of clusters, number of cooperative nodes and the constellation size are determined by a new established optimization model under the restrictions of compression model. Finally, simulation results show that the scheme can reduce the data gathering cost and prolong the sensor network's lifetime in a reliable guarantee of sensory data recovery quality.*

Keywords*: data gathering, compressive sensing, virtual MIMO, energy optimization*

1. Introduction

WSNs are typically self-organizing netwoks consisiting of nunmerous low-cost, feature riched and energy-limited sensor nodes, which can be widely applied in environmental monitoring, intelligent home furnishing, military monitoring, security monitoring and other fields [1, 2]. Such applications usually require that sensor nodes in surveillance region periodically sense data and report to sink noedes or base stations. So data gathering is an important operation to collect and transmit the sensed data to sink nodes. At present, WSNs have severe energy constraints, the problem for data gathering is that the transmssion of huge amounts of monitoring data causes large consumptions of nodes and reduces network life cycle.

Many CS-based data gathering methods have been studied to improve the energy efficiency of WSNs [3-11]. Chong Luo, et al., [3] applied CS theory to tree-based and chain-based data gathering in WSNs to obtain efficient data compression. In [4], You proposed a CS-based dynamic source and transmission control algorithm to prolong the lifetime of networks. In [5], a CS model for data gathering was proposed that used spatial and temporal relativity of signals. This model reduced the quantity of transmitted data and achieved better reconstruction performance in sink nodes. In [6] and [7], combined with random walk routing and CS measurement matrices, compressive data gathering schemes were proposed. In [8] and [9], CS was applied in clustered networks, cluster heads received raw data from their member-nodes and sent them to sink by the way of single-hop network. Besides that, some researches about sparse projections [10] and joint optimization of transport cost and recovery [11] in WSNs have had some useful explorations. These CS based methods can decrease cost by data compression and reducing the number of in-network data packets. But these researches are all based on transmission model with single input and single output.

As multi-antenna transmission in wireless networks can achieve spatial diversity. And spatial diversity is considered to be an effective solution to resist channel fading and reduce power consumption. Virtual MIMO mechanism with single-antenna nodes had been introduced in data gathering [12]. In [13] and [14], virtual MIMO was applied to improve data gathering cost in clustered wireless sensor networks. We can notice that above data gathering methods based on virtual MIMO need an effective data fusion, this mechanism will make systems more

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complex. Xu [15] proposed an optimized strategy of routing based on virtual MIMO for data gathering without fusion. However, there were only two nodes participating in cooperative transimission.

For CS-based data compression can be used to avoid data fusion for data gathering, we do some resrearches combing CS and virtual MIMO organically. This paper proposes a clustered energy-efficient data gathering method integrerting with CS and virtual MIMO for wireless sensor networks (CS-vMIMO). We first construct a system model for data gathering combing with CS and virtual MIMO. In this model, a sparse measurement matrix with LDPC-like coding structure is used to simplify compression and reduce the data amount. Secondly, an optimization model of minimal data gathering cost is proposed in sink to determine *the number of clusters, number* of cooperative nodes and constellation size. *To* ensure the reconstruction without distortion, the number of measurements and row weight are set to be constraints in the optimization model. Our simulation results illustrate that the proposed CS-vMIMO scheme effectively decreases the energy consumptions compared with the compressive data gathering with single-antenna nodes and other non-compression schemes.

The rest of this paper is organized as follows. In Section 2, we describe the system model and propose the energy optimization model. Section 3 presents the numerical results and discussion. And conclusion is drawn in Section 4.

2. Detailed CS-vMIMO Scheme

2.1. System Model

We assume that N sensor nodes have been randomly deployed in monitored area. The network is divided into n_c non-overlapping clusters. Each node except sink is energy-limited and equip with single antenna. And these nodes can share antennas of each other to generate a virtual MIMO. The data compression adopts distributed compressive sensing, each node is assigned a column vector of measurement matrix. The sink node has no energy constraints and has powerful processing ability. The sink node is used to execute energy optimization, data aggregation and reconstrucion. In order to describe conveniently, we define this scheme as CS-vMIMO. The network model of CS-vMIMO is described in Figure 1.

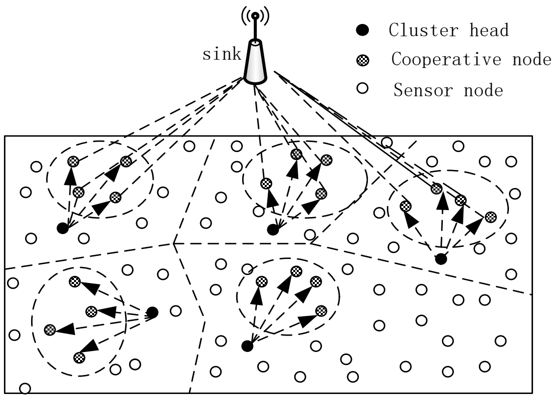


Figure 1. The Network Model of Data Gathering with Virtual MIMO

The operation processes of CS-vMIMO scheme are described in follows:

Preliminary: Construct measurement matrix, select cluster heads, form clusters, select appropriate cooperative nodes.

Data acquisition and measurement: Each node collects the real-time monitoring data, and carries out encoding measurement simultaneously by preallocated a column vector of measurement matrix.

Data trasmission: Each sensor nodes transfer its measured values to its respective head node in term of time slot. Head nodes receive the data from member nodes and execute an addition operation on data. Each cooperative node acquires data from respective head node and transfer to sink.

Reconstruction: Sink node receives data from all cooperative nodes, decodes and recovers the original data.

The CS-vMIMO data gathering scheme carries out by round periodically, each round contains above four phases. Specific slot assignments are shown in Figure 2.

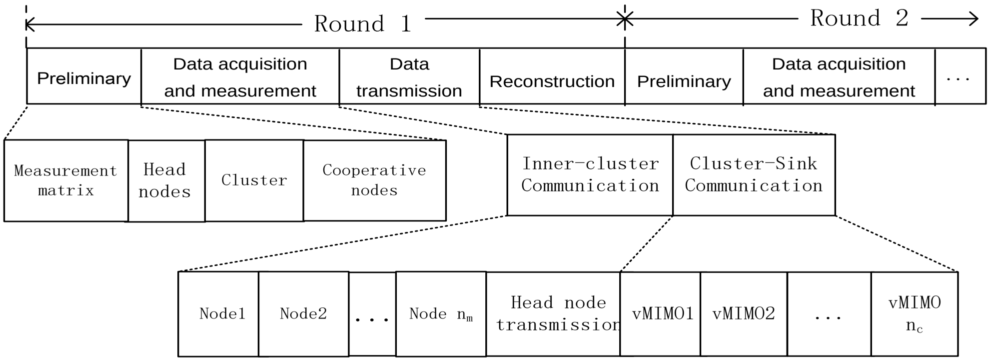


Figure 2. Slot Assignment of CS-vMIMO Data Gathering Scheme

In preliminary pahse, the construction of measurement matrix must be guaranteed against accurate recovery in sink node. We will give a detailed explanation in Section 2.1. In this paper, the selection of cluster head and cluster formation are determined by traditional LEACH protocol. Each cluster head decides cooperative nodes in internal cluster according to every member node’s residual energy.To minimize the energy consumption, number of head nodes and cooperative nodes are determined by a proposed energy cost model in the sink node. The analysis and optimization for system energy consumptiom will be described in more detail in the subsequent sections.

In data acquisition and measurement phase, all nodes acquire and measurement data in parallel. Measured values are temporarily saved to sensor memory.

In data transmission phase, the communications between sensor nodes and their head nodes, head nodes and their cooperative nodes within a cluster are defined as a inner-cluster communication. And the communication between cooperative nodes and sink node is defined as cluster-sink communicaiton. Inner-cluster communication and cluster-sink communication have different energy formulas because of fading and different distance.

In reconstrction phase, the recovery algorithm is crucial, it should be designed according to the measurement matrix.

2.2. Data Acquisiton and Measurement Matrices

Sensor nodes collect the monitoring datas and multiply their datas to measurement vectors. From the point of improving energy efficiency of data gathering, sparse measurement matrices have been applied in an attempt to the field of data gathering to decrease cost [16]. And LDPC-like measurement matrix has a sparse coding construction and has been suceessfully used in CS [17], number of nonzero elements is fewer and nonzero elements are equiprobably equal to 1 or -1. So we introduce LDPC-like measurement matrix in data gathering.

The sensory datas of N nodes in monitoring area can be considered as an N-dimensional vector $X(t)=\left[x_1(t),x_2(t),\cdots,x_N(t)\right]$ at the t^{th} data gathering round. $x_j(t)$ is the acquired data value of the j^{th} sensor node at the t^{th} round. Measurement matrix Φ is an $M\times N$ sparse random matrix with LDPC-like coding structure. Each node saves a column vevtor of measurenment matrix. In the t^{th} data gathering round, the meaured value of the j^{th} sensor node is:

$$y_{M\times j}(t)=\Phi_{i\times j}\cdot x_j(t)\big|i\in[1,2\cdots,M]=\left[\Phi_{1j}x_j(t),\Phi_{2j}x_j(t),\cdots,\Phi_{Mj}x_j(t)\right]^T \quad (1)$$

Head nodes add the measured values of its member nodes together. In the t^{th} round, measured data gathered by the m^{th} head node is:

$$\underline{y}_m(t)=\sum_{j=i}^{i+n_m-1}y_{M\times j}(t)=\left[\sum_{j=i}^{i+n_m-1}\Phi_{1j}x_j(t),\sum_{j=i}^{i+n_m-1}\Phi_{2j}x_j(t),\cdots,\sum_{j=i}^{i+n_m-1}\Phi_{Mj}x_j(t)\right]^T \quad (2)$$

Where n_m is number of nodes in the m^{th} cluster. $\underline{y}_m(t)$ is an M-dimension column vectors.

Sink node adds the measured values of different clusters together. In the t^{th} round, measured data gathered by the sink node is:

$$Y(t)=\sum_{m=1}^{n_c}\underline{y}_m(t)=\left[\sum_{j=1}^{N}\Phi_{1j}x_j(t),\sum_{j=i}^{N}\Phi_{2j}x_j(t),\cdots,\sum_{j=1}^{N}\Phi_{Mj}x_j(t)\right]^T=\Phi X(t) \quad (3)$$

Any i^{th} row vector of measurement matrix Φ is random vector with weight of r, 1 and -1 appear alternately. The column weight of measurement matrix Φ is defined as l.

We will do energy consumption analysis in the nexit section based on above system model and measurement matrix. Because sink node has no energy constrant, energy consumption of sink node is without considering. There is no complex signal processing in front-end nodes, and comparing with transmission cost , the energy of signal processing is ignored in next analysis. The energy of CS-vMIMO data gathering system is divided into two parts: the energy of the inner-cluster communication $E_{inner-cluster}$ and the cluster-sink communication $E_{to-\sin k}$. Each part is consists of two main components. One is consumption for all power amplifiers E^{PA}, the other is consumption for all circuit blocks E^{C}. We have the following energy expression:

$$\begin{cases}E_{inner-cluster}=E^{PA}_{inner-cluster}+E^{C}_{inner-cluster}\\ E_{to-\mathrm{sink}}=E^{PA}_{to-\mathrm{sink}}+E^{C}_{to-\mathrm{sink}}\end{cases} \quad (4)$$

2.3. Energy Consumption of the Inner-cluster Communication

The energy consumptionof different circuit components has been given by Cui, et al., [18, 19]. The power consumption of transmitter is expressed as:

$$P^{\mathrm{TC}}=P_{DAC}+P_{mix}+P_{filter}+P_{sys} \quad (5)$$

The power consumption of receiver is expressed as:

$$P^{RC}=P_{LNA}+P_{mix}+P_{IFA}+P_{filter}+P_{sys}+P_{ADC} \quad (6)$$

Where P_{DAC}, P_{mix}, P_{filter}, P_{sys}, P_{LNA}, P_{IFA} and P_{ADC} are the energy consumption for the digital-to-analog converter, the mixer, filter circuits, the frequency synthesizer, the low noise amplifier, the intermediate frequency amplifier and the analog-to-digital converter respectively.

In inner-cluster communication, the wireless signal is assumed to experience a square-law path loss, the transmission power is expressed as follow [18]:

$$P^{TPA}=-2(1+\alpha)N_f B\sigma^2\ln\left(\bar{P}_b\right)\frac{\left(4\pi d_{in}\right)^2 M_l}{G_t G_r\lambda^2} \quad (7)$$

Where $\alpha=\frac{\varepsilon}{\eta}-1$, ε is the Peak-to-Average Ratio (PAR) , η is the drain efficiency of the RFpower amplifier, B is the bandwidth of modulation system, σ^2 is noisy power spectral density, $\bar{P}_b$ is average bit error rate, d_{in} is the transmission distance , G_t and G_r are the gains of transmitter and receiver antenna respectively, λ is the carrier wavelength, N_f is noise coefficients of receiver, M_l is is the link margin compensating.

The energy consumption at the t^{th} data gathering round is the product of the power consumption and the average time. We denote every sensor node collects L_j bit data at the t^{th} round, ρ is compression ratio, $\rho=\frac{M}{N}$, β is the sparse rate of measurement matrix Φ, $\beta=\frac{r}{N}=\frac{l}{M}$. Based on LDPC-like measurement, each sensor node generates $\beta\rho N$ nonzero elements in every measured vector $y(t)$. At the t^{th} round , supporting the packet length of sensory data in the the j^{th} sensor node is L_j bits. The time required for transmitting by the j^{th} sensor node is:

$$T_j^s=\beta\frac{\rho N}{B\cdot b}L_j \quad (8)$$

Where b is the constellation size.

Because of using CS, each cluster head does not need data fusion and needs to send ρNL bits . The time required by the cluster head is:

$$T^h=\frac{\rho N}{B\cdot b}L \quad (9)$$

Where $L=\max\left\{L_j, j\in\left[1,2,\cdots,n_m\right]\right\}$. For the m^{th} cluster, the total energy consumption at the t^{th} round for a fixed-rate is:

$$E_{inner-cluster,m}=\sum_{j=1}^{n_m}\left(P^{TPA}+P^{TC}+P^{RC}\right)T_j^s+\left(P^{TPA}+P^{TC}+M_T P^{RC}\right)T^h \quad (10)$$

The first part of above fomula defines the energy consumption of communication from snsor nodes to head node within a cluster, the latter part of fomula (10) defines the energy consumption of communication from head node to cooperative nodes within a cluster. M_T is number of transmitters in vMIMO sysytem.

The transmission in iner-cluster is implemented with binary phase shift keying (BPSK), $b=1$. The time parameters are brought into the energy consumption formula (10), the total energy consumption at the t^{th} round for a fixed-rate can be rewritten:

$$E_{inner-cluster,m}=\frac{\rho N}{B}\left[\left(P^{TPA}+P^{TC}\right)\left(\sum_{j=1}^{n_m}\beta L_j+L\right)+P^{RC}\left(\sum_{j=1}^{n_m}\beta L_j+M_T L\right)\right] \quad (11)$$

2.4. Energy Consumption of the Cluster-Sink Communication

Because the communication from cooperarive nodes to sink node is a long distrance transmission, the channel is κ-order Rayleigh Flat-fading and multilevel quadrature amplitude modulation (MQAM) is adopted. In a long ditance transmission, the transmission power of cooperative nodes is:

$$P^{TPA\text{-}\sin k}=\left(1+\alpha\right)\bar{E}_b Bb\frac{\left(4\pi\right)^2 d_{to-\sin k}^{\kappa}}{G_t G_r \lambda^2}M_l N_f \quad (12)$$

Where $\bar{E}_b$ the total energy consumption per bit, $d_{to-\sin k}$ is the ditance from cooperative node to sink node:

$$\bar{E}_b=\frac{2}{3}\left(\frac{\bar{P}_b}{4}\right)^{-\frac{1}{M_T M_R}}\frac{2^b-1}{b^{\frac{1}{M_T M_R}+1}}M_T N_0 \quad (13)$$

Where N_0 is the single-sided noise power spectral density, M_R is number of transmitters in vMIMO sysytem.

At the t^{th} round , the time required by the i^{th} vMIMO array is:

$$T^{to-\sin k}=\frac{\rho N}{RBb}L \quad (14)$$

Where R is a correction factor for cooperative transmission. The power consumption of transmitter is same to Section 2.3. For the m^{th} cluster, the total energy consumption at the t^{th} round in the cluster-sink communication is:

$$\begin{aligned}E_{to-\text{sink},m}&=\left(P^{TPA\text{-}\sin k}+M_T P^{TC}\right)T^{to-\sin k}\\&=\left[\frac{2}{3}(1+\alpha)\left(\frac{\bar{P}_b}{4}\right)^{-\frac{1}{M_T M_R}}\frac{2^b-1}{b^{\frac{1}{M_T M_R}+1}}M_T N_0 Bb\frac{\left(4\pi\right)^2 d_{to-\text{sink}}^{\kappa}}{G_t G_r\lambda^2}M_l N_f+M_T P^{TC}\right]\frac{\rho N}{RBb}L\end{aligned} \quad (15)$$

2.5. Joint Optimization Model of the Total Cost

According to the results of above analysis, the total energy consumption of CS-vMIMO data gathering systmen at the t^{th} round is:

$$E_{total}=\sum_{m=1}^{n_c}\left(E_{inner-cluster,m}+E_{to-\text{sink},m}\right) \quad (16)$$

Synthesizing the formula (11), (15) and (16), the compression ratio ρ, the sparse rate of measurement matrix β,the constellation size b ,the number of coopertive nodes M_T and clusters n_c are variables of energy consumption formula (16). The energy consumption formula (16) is taken as the objective cost function, optimizes these parameters jointly.

$$(n_c, M_T, b) = \arg\min_{\substack{\rho \ge const. \\ \beta \ge const.}} E_{total} \tag{17}$$

Where the values of β and ρ should be set to satisfy the quality of CS reconstructed. Base on [17], β can be reduced if the number of measurements is increased accordingly. The optimization problem of formula (17) can be solved by integer programming. In practice, the parameters (n_c, M_T, b) are calculated in advance, then the data gathering work is carried out periodically. When channel fading characteristics are unchanged, above jiont optimization is not need at each round.

3. Numerical Results and Analysis

This section presents the numerical results to demonstrate the energy efficiency of the proposed CS-vMIMO scheme. We support there are 500 nodes ($N = 500$) uniformly distributed in $100m \times 100m$ monitor area. The data collected by sensor nodes is K-sparse signal or has a sparse representation under a base. K is difined as a sparsity, $K = \|X(t)\|_0$. This section shows the following numerical results: the sensory data recovery quality under different number of measurements and the energy consumption of the CS-vMIMO data gathering scheme.

3.1. Recovery Quality Under Different Measurement Numbers

The number of measurements is a major factor for recovery quality in CS. And according to energy analysis in Section 2, it also influences energy consumption of data gathering. We now evaluate the recovery quality of LDPC-like compression model under different measurements and row weiths. We define the reconstruction error as a normalized error $\|X - \hat{X}\|^2 / \|X\|^2$. The data collected by sensor nodes is 25-sparse signals, we compare the recovery quality with $\beta = 0.064$ and $\beta = 0.032$ under different measurement numbers. The reconstrution algorithm adopts the algorithm in [20].

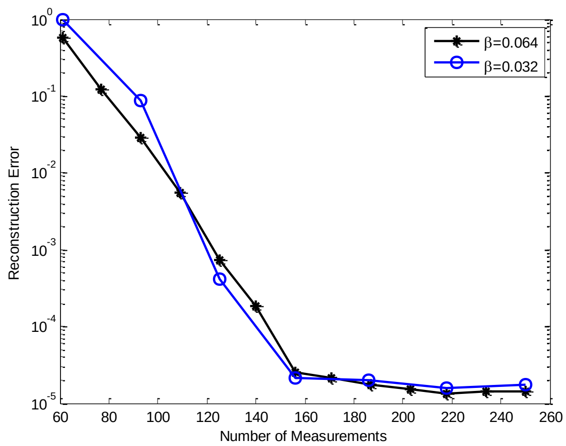


Figure 3. The Reconstruction Error under Different Measurements

Figure 3 shows that two curves have similar properties when the number of measurements is sufficient. When the nunmber of measurements is less, the value of β can impact the reconstruction error. The target error is set to be 0.1 to ensure quality of recovery, we can get the combination of different β and ρ ($\rho = M/N$). The number of measurements required to reach the target error: $M = 77$ and $M = 93$ corresponding to $\beta = 0.064$ and $\beta = 0.032$ respectively. The following energy optimization also should be carried out under the constrants of (β, ρ).

3.2. Energy Consumption Evaluation and Analysis

In this section, we evaluate the energy-efficient performance of our CS-vMIMO scheme. The values of different parameters, shown in Table 1, are adopted from [18].

Table 1. Values of Simulation Parameters[18]

$P_{DAC} = P_{ADC} = 15mW$	$P_{mix} = 30.3mW$	$P_{filter} = 2.5mW$
$P_{syn} = 50mW$	$P_{LNA} = 20mW$	$P_{IFA} = 30mW$
$N_f = 10dB$	$\sigma^2 = -174dBm/Hz$	$M_l = 40dB$
$G_t G_i = 5dBi$	$\lambda =$ 0.12m	$\overline{P}_b = 10^{-3}$
$\varepsilon = 3\left(\sqrt{2^b} - 1\right)/\left(\sqrt{2^b} + 1\right)$	$\eta = 0.35$	$B = 10kHz$

To better illustrate the influences of cooperative node numbers, constellation size and number of clusters, the simulations are executed using above three variables respectively.

Figure 4 shows the curves of transmission dsitance and the energy consumption, with number of cooperive nodes are 2,4 ,8 and single-input single-output (SISO), non-cooperative transmission. We set $\beta = 0.064$, $\rho = 0.16$, the fading factor κ from cooperative nodes to sink is 2.5, the modulation is QAM, the constellation size $b = 5$. From the Figure 4, we can see that an energy-efficient number of cooperative nodes is exist according to a certain transmission distance and the parameter M_T could influence the total energy.

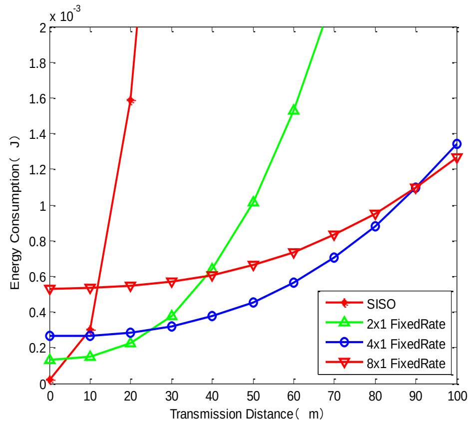


Figure 4. The Energy Consumption under Different Distances

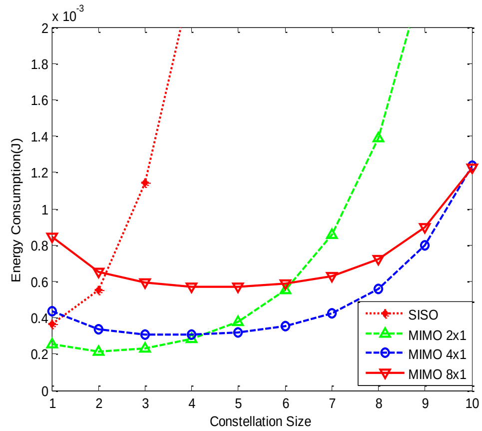


Figure 5. The Energy Consumption under Different Constellation Sizes

Figure 5 shows the curves of constellation size and the energy consumption. The transmission distance is fixed to 30 meters. We can see from Figure 5, there is an optimum constellation size b for every number of cooperative node. Except the constellation size, other parameters is same to Figure 4. Figure 6 shows the curves of cluster number and the energy consumption, with number of cooperative nodes are 2,4 and 8. The clustering protocol is adopted traditional LEACH. The constellation size is fixed, and the sink node lies in the coordinate of $(100,175)$. From Figure 6, the number of clusters also has an effect on the energy consumption.

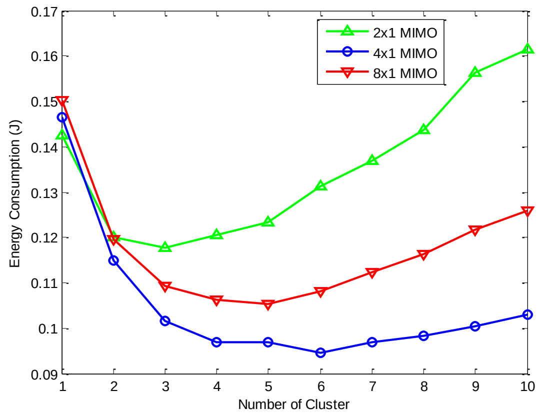
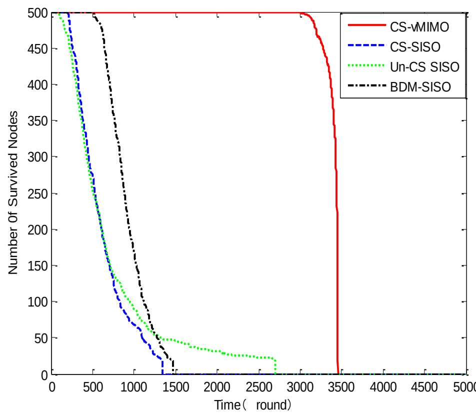
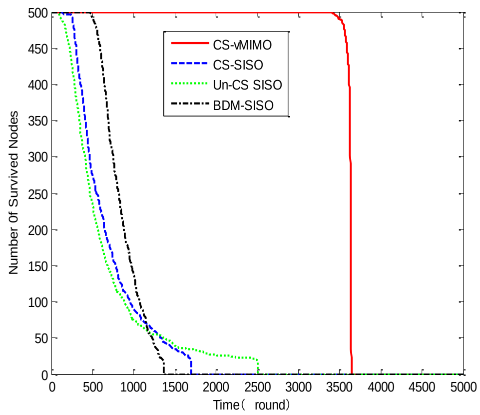


Figure 6. The Energy Consumption under Different Clusters



(a) $\beta = 0.064$, $\rho = 0.16$



(b) $\beta = 0.032$, $\rho = 0.19$

Figure 7. Comparisons of Node Survival Time

As described, The number of cooperarive nodes M_T, the constellation size b and the number of clusters n_c can influence the energy consumption repectively. Next we will show the results of joint optimization. In order to demonstrate the performance of the proposed CS-vMIMO scheme in energy efficiecy, we compare this scheme to several other kinds of data gathering schemes. The simulation results are shown in Figure 7. CS-vMIMO is the proposed data gathering scheme in this paper, CS-SISO is the compressive data gathering scheme with LDPC-like matrix and SISO transmission, BDM-SISO is the compressive data gathering scheme with BDM measurement matrix proposed in [9], and Un-CS SISO is the data gathering with non-compression and SISO transmission. The sink node lies in $(100,175)$ outside the monitor area. We simulate the lifetime of nodes. The number of clusters, cooperative nodes and constellation size are joint optimized under the constrants of β and ρ in the CS-vMIMO scheme. In Figure 7(a) and Figure 7(b), $\beta = 0.064$, $\rho = 0.16$ and $\beta = 0.032$, $\rho = 0.19$ respectively. From Figure 7, comparing to other CS-based data gathering scheme, the CS-vMIMO scheme postpones the emergency of the first dead node, enhances the network energy balance and prolongs the lifetime of neworks. We have noticed that, for different values of $(\beta, \ \rho)$, the jiont optimization results is also different and the CS-vMIMO scheme with $\beta = 0.032$, $\rho = 0.19$ prolongs the life cycle of networks about 300 rounds comparing to the scheme with $\beta = 0.064$, $\rho = 0.16$. This is because in Figure 7(b), the selection of the $(\beta, \ \rho)$ is better than it in Figure 7(a), less measurement of sensor nodes is still able to ensure the quality of reconstruction. So the parameters of measurement matrix will affect the energy consumption of data gathering.

4. Conclusion

CS and virtual MIMO both are efficient ways to decrease the energy consumption of data gathering. We propose and analyse an energy-efficient data gathering scheme by intergating LDPC-like compressive sensing and virtual MIMO. We construct the CS-vMIMO data gathering system, discuss the measurement matrix , analyse the energy consumption of CS-vMIMO, and present the joint energy consumption optimization model. Our simulations have shown that the CS-vMIMO has high energy-efficiency. But in this paper, we only consider the single-hop routing. Next, we will further optimize the energy consumption by combinating muti-hop routing protocol.

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